Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 25 (2011) 84 – 87

Procedia Engineering

www.elsevier.com/locate/procedia

Proc. Eurosensors XXV, September 4-7, 2011, Athens, Greece

Cooperative 3D Air Quality Assessment With Wireless Chemical Sensing Networks

Saverio De Vito[a], Grazia Fattoruso[a]*, Raffaele Liguoro[b], Antonio Oliviero[b], Ettore Massera[a], Carlo Sansone[b], Valentina Casola[b], Girolamo Di Francia[a]

[a]*ENEA – UTTP/MDB Dept. Portici Research Center. P.le E. Fermi, 1; 80055, Portici (Napoli), Italy.*
[a]*DIS Dept. – Università di Napoli "Federico II", Via Claudio,21; Napoli, Italy*

Abstract

Indoor Air Quality assessment is an emerging application field for chemical sensing due to raising concerns about indoor VOC pollution levels. Local and distributed assessment of chemicals concentrations is also significant for safety (gas spills detection, pollution monitoring) and security applications as well as for HVAC automation for energy efficiency. Mobile robot based and wireless sensor network based approaches are under investigation for providing efficient solutions. Here, we report results obtained by a network of wireless intelligent electronic noses in a semi-controlled environment for the detection of pollutants in complex mixtures . The w-noses are equipped with local discrimination and quantification capabilities sustained by trained artificial neural networks overcoming interferents issues. 3D chemicals concentration reconstruction is obtained by a sensor fusion algorithm at datasink on the basis of the w-noses responses.

Keywords: Intelligent sensors fusion, Wireless electronic noses, Indoor Air Qualityt, Distributed Chemical Sensing, Enviornmental monitoring

1. Introduction

The capability to detect and quantify chemicals concentration in 3D environments as well as locating possible gas spills, is becoming more and more interesting for the growing concerns about indoor environments safety and security.Just as an example, VOCs concentrations are frequently much higher in indoor environment like small offices and houses than outdoor due to degassing form furniture adhesives, special cleaning agents or cigarettes smoke. Unforunately, many of them (e.g. formaldehyde) are known to pose serious threats to humans health ranging from headaches to cancer. Chemical signal propagation characteristics make the use of the common single measurement point architecture mostly ineffective. Actually, the propagation of chemical plumes in real environments is primary subdued to complex fluid dynamics effects while diffusion effects appear to be negligible in most circumstances. We proposed to investigate the use of a mesh of wireless e-noses for quantitative indoor air quality assessment addressing architectural, power and on-board intelligence issues [1]. The proposed architecture could be applied to safety scenarios like spills detection (e.g. hydrogen spills in hydrogen refills stations). Authors like Diamond et al. have tackled the wireless chemical sensing scenario demonstrating the capability of detection of single sensor platforms in single chemical detection tests [2]. On the other hand, Liliental et al. pursued a mobile

doi:10.1016/j.proeng.2011.12.021

multi sensor robot approach addressing particularly the 3D source declaration problem [3]. Here, we investigate the possibility for on-board discrimination and quantification as well as 3D reconstruction of chemicals concentration maps for gas mixtures. In facts, in this study we pursue the 3D gas concentration mapping of acetic acid – ethanol mixtures (as VOC pollutant simulants) in ambient air by a mesh of wireless electronic noses coupled with a sensor fusion algorithm. Parameters tuning is also addressed with a cross validation approach.

2. Experimental and Methods

A set of 4 w-noses, each one relying on 4 MOX sensors array was developed using Figaro 2602, 2600, 2x2620 sensors. The sensors array have been assembled on a signal conditioning board and connected to a commercially available WSN platform (Crossbow TelosB mote) and then integrated in a compact plastic case for free gas flow operation. The TelosB mote is a TinyOS compliant platform equipped with a TI-MSP4300 low power µcontroller, a CC2420 zigbee capable radio and Hamamatsu digital T/RH sensors, it provide several A/D and D/A as well as digital I/O lines for sensors and peripheral connections. In order to ensure to ensure data acquisition, local processing and transmission capabilities, ad-hoc software components have been designed and developed in NESC, a component based, TinyOS supported, dialect of the C language. Standard routing mechanisms provided by TinyOS RTS have been also integrated in order to deploy a mesh topology w-nose network. At the data sink, a java based component provide data logging and rebroadcastimg features towards remote monitoring GUIs and sensor fusion software components.Initially, a complete instance of the 4(+2) sensors array has been calibrated using a controlled climatic chamber (described in ref. [4]). Synthetic air was used as a bubbling carrier for Acetic Acid and Ethanol at different relative humidity percentages (see Table 1). In this setup, sensor resistances have been sampled at 30s intervals. A 2-slots Tapped Delay Neural Network (TDNN) with 10 hidden layer neurons have then been trained and validated using leave-[1 exposure cycle]-out procedure (see [4]) for instantaneous concentration estimation. Mean Absolute Error (MAE) divided by concentration ranges, was computed for the evaluation of overall array performance. The MAE/range value was eventually found to be 2.34% (0.75ppm) for Acetic Acid and 6.5% (9.8ppm) for Ethanol (see fig. 1). These results encouraged us to proceed with the second experimental setup involving the deployment of the 4 complete w-noses network in an ad-hoc glass box (Volume=0.36 m^3) in order to evaluate their capability to reconstruct a real time 3D chemical concentration image of the two pollutants. Different amounts of the two chemicals (see table 2) have been introduced and diluted until complete evaporation with the use of a standard PC-fan. At steady state, based on the reasonable hypothesis of uniform concentration distribution over the box, for each of the deployed w-noses, the responses of the 4 chemical sensors to the gas mixture were sampled (1Hz) together with recorded environmental RH and temperature. The sampled values were used to build a suitable dataset for the training of pattern recognition algorithm devised to estimate pollutants concentrations. This dataset was, in facts, used to train a FFNN (Feed forward Neural Network) based two level classifier/regressor scheme that was then coded using NESC language and deployed on-board on each the wireless electronic noses. In this way, each of the w-nose was made capable to estimate the local pollutants concentration at its deployment location. Further 10 runs of steady state samples acquisition with the same procedure was then used to build a suitable test set. Kernel-DV algorithm (see [3]), originally developed by the Lilienthal group for the use with mobile robot acquisitions, was adapted for real time 3D sensor fusion in order to reconstruct a real time chemical concentration map of the two gases within the glass box. The algorithm use a a 3D Gaussian kernel to propagate localized measurement to a 3D environment based on confidence values depending on the point distance from the actual measurement points. Estimation based on the propagation are balanced with a default averaged value (homogeneous gas distribution) by the use of the confidence value that is normalized by a scale factor . Eventually, should confidence value fall to 0 (points located far from all actual measurement points) the algorithm revert to the homogeneous gas distribution hypothesis. In the last setup, 17 µg of Ethanol was let evaporate within the glass box in one of the left-down box corner. By using the neural calibration obtained before and encoded in the on board computational intelligence component , the single nodes were able to estimate local concentration of both gases. Their estimations were transmitted and collected at datasink where a sensor fusion component was coded to reconstruct an instantaneous 3D chemical image of the box.

3. Results and conclusions

As regards as the evaluation of steady state estimation performances for the single w-noses, MAE figures were computed by using the above mentioned test set. The MAE, averaged for all the 4 w-noses, reached 3.15ppm and 4.36ppm for ethanol and acetic acid, respectively. This figures allow us to locate the expected absolute error on the real-time local concentration estimation under a 5 ppm threshold. This value is valid for concentration estimation in a mixture, and so in presence of interferents, provided that concentrations levels have a slow variation rate. Overall performance of the 3D reconstruction algorithm depends on the value of three base parameters, i.e. cell mesh width, the kernel width σ, the confidence scale parameter and, of course, by the w-nose deployment positions. Cell mesh width only trade off 3D reconstruction resolution with computational costs, for this reason a fixed value that allowed for real time reconstruction has been selected. Confidence scale parameter depends on kernel width so, for a fixed deployment configuration of the w-noses, an automated procedure has been designed to choose the appropriate kernel width parameter value on the basis of a leave-one-mote out approach. Actually, scanning by brute force a parameter values array ([0.05, 0.10, 0.15, 0.2]), for each parameters setting, all but one sensing nodes have been used to estimate the concentration value of the two analytes, with the adapted Kernel-DV algorithm, at the remaining node position. Figure 3 shows the comparison between local instantaneous concentration estimation at node position 3 and estimation carried out by the 3D reconstruction algorithm at the same position. Without affecting generalization, the mean absolute difference between the estimated value and the actual value as estimated by the remaining node, during all the exposure time, has been defined as the performance value to be optimized by the brute force approach.

Table 1: The different gas mixtures used during the controlled chamber experimental setup were synthesized by using all combination of the reported concentration of Acetic Acid and Ethanol at different relative humidity for total 216 cycles. The baseline mixture was set at RH = 50%.

RH (%)	Gas Concentration Ranges	
	Acetic Acid (ppm)	Ethanol (ppm)
[20,30,50]	[0,5,7,10,15, 20,25,30,32]	[0,15,30,70,90, 115,130,150]

Table 2: The different gas mixtures used during the glass box experimental setup were synthesized by using all combination of the above reported concentration of Acetic Acid and Ethanol. For each combination, two different exposure cycles were executed. Steady state sensor array response to each exposure cycle was recorded to build the training dataset. Ambient RH values and temperatures (not controlled) were also recorded to be part of the on board NN feature set.

Gas Concentration Ranges	
Acetic Acid (ppm)	Ethanol (ppm)
[0,5,10,15,20]	[0,6,12,17,23]

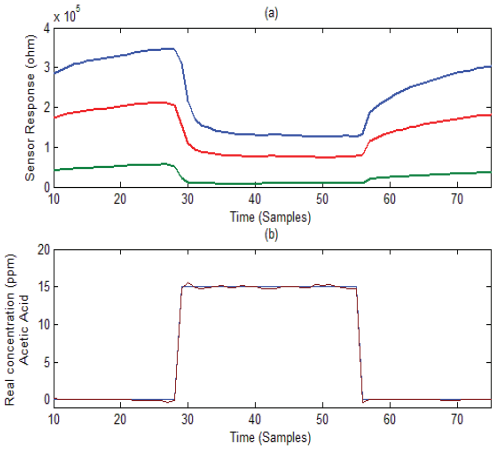

Figure 1: Sensor array responses in controlled chamber setup (a); Trained TDNN responses and Ground Truth comparison during the correspondent complete exposure cycle (b).

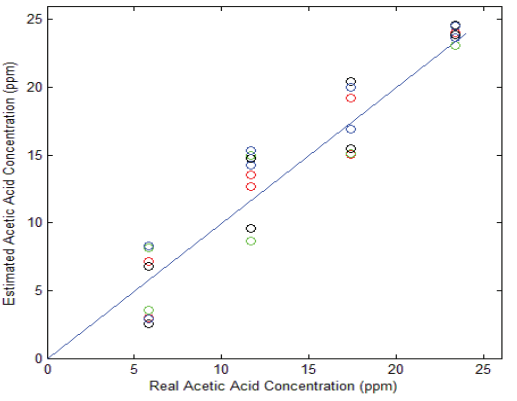

Figure 2: On Board neural network response versus actual Acetic Acid concentration in the glass box experimental setup, validated @ different acetic acid concentrations (range reported in table 2).

Figure 4 shows the averaged instantaneous absolute difference among local and 3D reconstruction based estimations for the 4 motes in the ethanol case. Peaks can be spotted in the uprise and downfall of the concentration levels during transients. The peaks can be explained by the different concentrations experimented by the motes during transients due to their different positions. In this case, the peaks magnitude could be effectively reduced by tuning mote positioning and density of the measurement mesh in the sensed environment. Figures 5 and 6 depicts, respectively, w-nose positioning and an instantaneous reconstruction of the concentration of the two pollutants.
This preliminary results shows the possibility to effectively use a w-nose deployment for real time 3D quantitative air quality analysis in presence of a pollutants mixture. The use of mote crossvalidation has been also shown for the sensor fusion algorithm parameter tuning and performance evaluation.

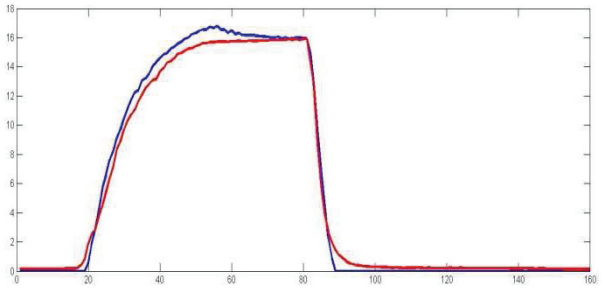

Figure 3: Instantaneous ethanol concentration estimation as computed at node 3 (blue) compared with the estimation obtained by 3D reconstruction, using the remaining 3 nodes, at the same location. The experimental setup foresee the deployment of 4 w-noses in the 0.36 m^3 glass box and the release of 17 microgram (20,9 ppm) of ethanol near one corner of the box.

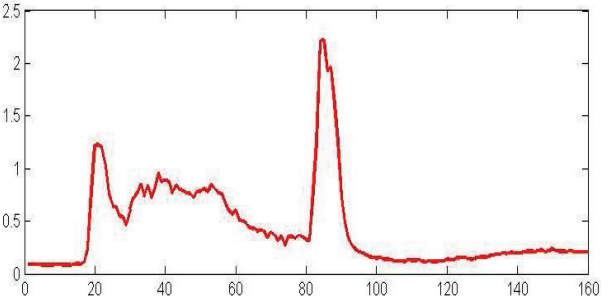

Figure 4: Instantaneous absolute difference among local ethanol concentration and 3D reconstruction algorithm with kernel width σ set at 0.1 value. The instantaneous difference reported here was averaged throughout the leave-one-mote-out procedure executed for the exposure to 17 microgram (20,9 ppm) of ethanol. The computed MAE value was used for the optimization of the 3D reconstruction algorithm.

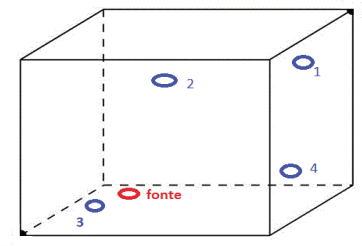

Figure 5: Positioning of the 4 w-noses and gas source within the glass box.

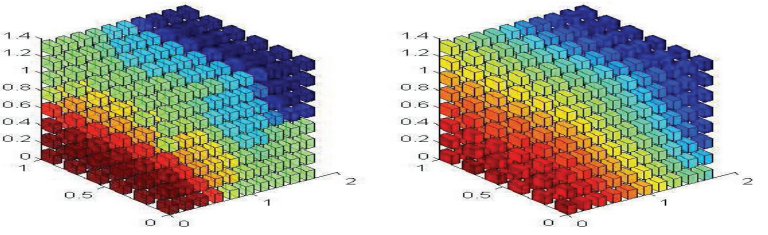

Figure 6: Istantaneous 3D ethanol (right) and acetic acid (left) concentration reconstruction (computed @ datasink) using a 4 w-nose deployment in the glass box experimental setup.

References

[1] De Vito, S. Di Palma, P. Ambrosino, C. Massera, E. Burrasca, G. Miglietta, M.L. Di Francia, G., Wireless Sensor Networks for Distributed Chemical Sensing: Addressing Power Consumption Limits With On-Board Intelligence, Sensors Journal, IEEE , vol.11, no.4, pp.947-955, April 2011.

[2] D. Diamond, S. Coyle, S. Scarmagnani and J. Hayes, Wireless Sensor Networks and Chemo/Bio-Sensing , Chemical Reviews, 108 Issue: 2 (2008) 652-679.

[3] A.Lilienthal, M. Reggente, M.Trincavelli, J. L.Blanco, J. Gonzalez, A Statistical Approach to Gas Distribution Modelling with Mobile Robots The Kernel DM+V Algorithm, Proc. of IEEE IROS Conf., 2009, 570-576.

[4] S. De Vito, A. Castaldo, F. Loffredo, E. Massera, T. Polichetti, I. Nasti, P. Vacca, L. Quercia, G. Di Francia, Gas concentration estimation in ternary mixtures with room temperature operating sensors using tapped delay architectures ,Sensors and Actuators B: Chemical Vol. 124, Issue 2, 26 June 2007, Pages 309-316.